# VALUE-ADDED STRATEGIES IN THE SPECIALTY CROP INDUSTRY: EXPLORING FARMERS' DRIVERS AND STRATEGIES AT THE FARM LEVEL

by

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**A Thesis**

*Submitted to the Faculty of Purdue University*

*In Partial Fulfillment of the Requirements for the degree of*

**Master of Science**

Department of Horticulture and Landscape Architecture

West Lafayette, Indiana

May 2021

**THE PURDUE UNIVERSITY GRADUATE SCHOOL**
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# ABSTRACT

Value-added (VA) technologies can help farmers in the specialty crop industry generate new products, increase off-season income sources, expand market access, and improve overall profitability. These technologies can support the development of rural economies through the generation of new businesses and job creation. The USDA defines VA products as those 1) changed physical, 2) produced in a manner that enhances their value, and 3) physically segregated in a manner that results in enhancement of their value. Drawing from this definition, this study investigated VA technologies such as drying, cutting into customer-ready portions, washing and labeling specialty crops. The objectives of this study are threefold. First, we analyze how market access and diversification drive specialty crop farmers to adopt VA technologies. Second, we address the potential endogeneity between the adoption of VA technologies (vertical diversification) and the number of crops (horizontal diversification). Lastly, we investigate how market access drives farmers to utilize food labels for VA products. Data for this study came from a 2019 web-based survey of specialty crop farmers. A total of 766 farmers completed the survey, with a response rate of 21.5%. The questionnaire included questions related to farmer's demographics (i.e., educational attainment, gender, farming experience), farm characteristics (i.e., crops, markets, and growing technologies), and farmers' beliefs regarding their farm system. Results suggest that market access is a significant driver of VA technology adoption. Also, the size of the farm, networks, farmer's perceptions, and employment growth influence adopting VA technologies. The results also show us that farmers adopting VA technologies tend to experience economic growth.

# CHAPTER 1. INTRODUCTION

U.S. agriculture has shifted from resource-led growth to productivity-led growth in the last few decades (USDA-ERS, 2017). The focus on agricultural development has shifted from increasing the amount of land, water, labor, capital, and other inputs to the improvement of the total factor productivity (TFP) of these resources. TFP is a measure of efficiency in which input utilization results in output (Cusolito and Maloney, 2018). The importance of the TFP growth in agriculture is related to the fact that most agricultural inputs have a limited supply, and changes in their use can cause instability in the ecosystems that can lower yields (Foley et al., 2005). This productivity growth in agriculture has allowed food to become more abundant and cheaper in the last 50 years, even as the world population has more than doubled (Fuglie and Rada, 2013).

Farm productivity goes beyond yield increases and input and cost decreases; productivity growth also focuses on the efficient utilization of agricultural resources. For example, increasing productivity includes the diversification of farming outputs by adopting value-added (VA) agriculture (Cusolito and Maloney, 2018). Farmers adopting VA technologies can use resources more efficiently in their agricultural operations. Through the adoption of VA technologies, farmers can use innovative production methods that improve the characteristics of their products, such as organic practices, and undertake post-harvest procedures that can increase food production, reduce food waste and loss, and receive price premiums such as drying, cutting or washing their harvest (Cusolito and Maloney, 2018). That is why adopting VA technologies and practices is likely to be a key driver to increase TFP and income in agriculture (Fuglie, 2010).

Federal and local government initiatives have been encouraging the adoption of VA technologies to stimulate new enterprises and increase innovation in agriculture (Knudson et al. 2004). Innovation has been defined as introducing a new good, process, market, or source of raw material or implementing a change in an existing production process (Schumpeter, 2000), and innovations are carried out by entrepreneurs (Kirzner, 1979). One of the first categorizations of VA technologies as agricultural innovations was processing raw products such as wine production from grapes farms (Amanor-Boadu, 2003).

While farmers adding value to their products may face increased risks, they are typically rewarded with higher revenues than their commodity-producing counterparts (Brees et al., 2010). Beyond increasing product differentiation and farm revenue, the adoption of VA technologies tends to generate spillover effects by contributing to rural economic growth. Counties with greater reliance on agriculture tend to experience less economic growth than those with lower dependence, except for counties reporting a more significant share of VA agriculture (Monchuk et al., 2007). Drabenstott and Meeker (1997) reported that increasing revenues from VA technologies benefit the farmer and tend to be distributed throughout their communities and directly impact economic growth (Drabenstott and Meeker, 1997).

The importance of the specialty crop industry is derived from the increased production and demand for specialty crops in the past decades (USDA-ERS, 2019). To illustrate, the market value of fruits and vegetables increased by 134% and 77% in the 1995-2016 period, respectively (Minor and Bond, 2017). According to the 2017 Census of Agriculture (USDA-NASS, 2020), specialty crops sales reached over $87.6 billion. The same census reported over 242,818 operations growing vegetables, citrus, and noncitrus crops comprising nearly 15.6 million acres. The 2017 Census of Agriculture reported 33,523 farms sold over $4 billion in VA products in 2016, of which $2 billion accounts for horticultural specialties VA products. Nevertheless, these sales are just a tiny portion of the $877 billion in sales reported by around 30,000 U.S. food and beverage manufacturing (USDA-NASS, 2020).

Low et al. (2020) proposed that farmers tend to adopt VA technologies as a strategy to diversify on-farm income (push effect) or as a response to demand trends on differentiated food products (pull effect). In other words, farmers can be pushed by improvements in production technologies and pulled by the increasing consumer demand for fresh produce (USDA-NASS, 2020). More recently, VA produce does not have to go through a physical transformation; farmers can adopt VA technologies by improving the attributes of their produce via food labels such as organic, local, or chemical-free (Womach, 2005; Ernst and Woods, 2011).

Cirera and Maloney (2017) described the agriculture innovation paradox as follows: "*why, if returns to the adoption of new technologies are so high, so few farmers adopt them?*". Recent literature on VA technology adoption posed farmers can be deterred to innovate due to lack of information, production systems, finance, and market (Clark, 2020). These findings suggest that no single constraint can explain the lack of adoption of VA technologies in the specialty crop industry, and multipronged approaches may be necessary to accelerate the understanding of why farmers adopt VA technologies.

This study investigates the adoption of VA technologies. We follow the U.S. Department of Agriculture (USDA) definition of VA technologies (USDA Rural Business Development, 2017). First, the product has changed the physical state. For example, grapes transformed into wine or the processing of fresh vegetables to make salsa. Second, the product has to be produced to enhance the value of the agricultural product (i.e., organically produced products). Lastly, the product has to be physically segregated in a manner that results in the enhancement of the value of the agricultural product. For example, the use of food labels (e.g., certified organic, chemical-free, locally grown, and state-produced labels) enhances the marketing system of an agricultural operation. We categorized VA technologies as drying, cutting, washing, and labeling specialty crops.

Little research has been conducted about the drivers of adopting VA technologies in the specialty crop industry in the U.S., and most research on VA technology adoption has focused on the county, state, or regional level (Monchuk et al., 2007). This study focuses on the factors influencing specialty crop farmers to adopt VA technologies at the farm level. The hypotheses of this study are the following: (1) market access increases the farmer's likelihood of the adoption of VA technologies, (2) Increasing the number of crops produced to increase the probability that farmers adopt VA technologies, and (3) Market access increases the farmer's likelihood of adopting food labels for VA products.

The objectives of this study are threefold. First, we analyze how market access affects farmer's decision to adopt VA technologies. Asfaw (2011) and Ruslan et al. (2013) reported the link between agricultural innovations and market access. They proposed that through increased market access, farmers obtain information on consumers' preferences leading them to differentiate their products through technology adoption. According to Boland et al. (2009), the information provided by the market determined where and when to consider opportunities to adopt VA technologies. The key explanatory variable in this study is the vector *market access* in Eq. (1). We use the Herfindahl index to proxy as *market access* (Gollop and Monahan, 1991), and the equation is decomposed into two components: number of sales methods used (first bracket: *market diversification index*) and distribution of sales per method (second bracket: *market distribution index*). See *section 3.2.1* for a complete explanation of the equation. We expect that farmers selling directly to consumers are more likely to receive feedback on product presentations and labels and motivate them to invest in VA technologies.

Second, we address the potential endogeneity between the adoption of VA technologies (vertical diversification) and the number of crops (horizontal diversification). Using results from a robust instrumental variable (IV) approach, we propose that the number of crops among specialty operations influences the adoption of VA technologies and not the other way around. In other words, we propose that by increasing the number of produced, transformed, and sold crops, farmers are encouraged to adopt VA technologies to increase efficiency and productivity. Third, farmers use food labels to transmit information about their production processes and handling practices and differentiate their products (Roe and Sheldon, 2007). Thus, we took the next step, and we investigate how market access drives farmers to utilize food labels for VA products. We categorize farmers as those not adopting VA technologies, those adopting VA technologies, and those using food labels for VA products.

Results provide policymakers, Extension agents, farmers, and researchers with empirical evidence about key drivers and barriers in the VA technologies adoption process. For example, the categorization of VA farmers can support the adoption of these technologies through better-targeted policies and strategies to contribute to the productivity growth of the agricultural sector in the U.S. These findings can help the government improve the efficiency of the funds dedicated to supporting rural development through agriculture. Extension agents can use our results to provide improved training to farmers towards VA technologies. Extension personnel can help to lift the barriers farmers face when adopting VA technologies. Researchers can use our findings to further improve the understanding of farmers' decision-making and continue to contribute to the long-term productivity and sustainability of the agricultural sector. The results of this study can be helpful to assist farmers by incentivizing the drivers and help them overcome the barriers to adopt of these types of technologies.

# CHAPTER 2. LITERATURE REVIEW

## 2.1 Framing the Adoption of Value-Added Technologies

Value-added agriculture has been framed in ways that encompass the diffusion and use of technologies that help the farmer increase the value of farm products. According to Ernst and Woods (2011), VA technologies range from agri-tourism activities carrying out transformation processes for specialty crops. Value-added technologies were first introduced to process raw produce as washing, cutting into ready-to-consume portions, and drying produce (Amanor-Boadu, 2003). In recent times, value-added produce does not have to get through a physical transformation; farmers can adopt value-added technologies by improving the attributes of their goods. For example, labeling produce as organic, local, or chemical-free has been considered crucial VA strategies to access price premiums (Womach, 2005; Ernst and Woods, 2011).

According to Amanor-Boadu (2003), VA technologies have to satisfy at least one of the two following conditions: (1) if one is rewarded for performing any activity that has traditionally been performed at another stage further down the supply chain; or (2) if one is rewarded for performing an activity that is discovered to be necessary but has never been performed in the supply chain. Coltrain et al. (2000) conceptualized VA agriculture as economically adding value to a product by changing its current place, time, and characteristics to others more preferred in the marketplace.

Lu and Dudensing (2015) proposed VA agriculture as a portfolio of agricultural practices that enable farmers to align with consumer preferences for agricultural or food products with form, space, time, identity, and quality characteristics that are not present conventionally produced raw agricultural commodities. In other words, changing their position in the supply chain (i.e., from producer to processor or retailer), creating closer or direct linkages between themselves and consumers, or changing production processes to alter or preserve specific intrinsic characteristics of their farm/ranch products can be characterized as VA agriculture. Also, Womach (2005) refers to VA agriculture as the adoption of manufacturing processes that increase the value of primary agricultural goods. VA agriculture has also been referred to as increasing the economic value of a commodity through particular production processes (e.g., organic production) or regionally branded products that increase consumer appeal and willingness to pay a premium over similar but undifferentiated products.

This study follows the USDA Rural Business Development definition of VA technologies (USDA Rural Business Development, 2017). According to the USDA, VA products are defined as follows: The first and most common approach involves changing the physical state of produce, such as changing the physical state of strawberries by transforming them into jam or the processing of fresh vegetables make salsa. The second approach includes the change in the production practices that enhance the value of the agricultural product, such as organically produced products. Lastly, VA products have been physically segregated in a manner that results in the enhancement of the value of the agricultural product. To illustrate, the use of food labels (e.g., certified organic, chemical-free, locally grown, and state-produced labels) enhances the marketing system of an agricultural operation.

## 2.2 Entrepreneurship and Innovation as Drivers of Adoption of VA technologies

Schumpeter (2000) characterized innovation as the introduction of a new good or new quality of a good, the introduction of a new method of production, the opening of a new market, the acquirement of a new source of raw material, or by carrying out a change of an existing industry structure. As proposed by the researcher, innovation does not necessarily mean the creation of a new product. On the other hand, the Austrian School defined entrepreneurs as those who can take advantage of imperfections in market information to make innovations (Kirzner, 1979). In this way, innovations move markets from disequilibrium to a new equilibrium (Kirzner, 1979).

Entrepreneurship has also been widely studied in business, management, and psychology literature. According to Knight (1987), entrepreneurs are highly motivated individuals who are moved to start new ventures, launch new products, or open new markets with an intense desire to build something of their own. Entrepreneurs are also described as perceptive and goal-oriented to spot business ideas (Learned, 1992; Mitton, 1989). Entrepreneurs are habitually dominant to influence others to do what they want to be done and direct the activities of subordinates (Neider, 1987). Some researchers believe that entrepreneurs are born, not made (Cohen, 1980). However, extensive literature suggests that entrepreneurship is shaped by the interaction of personal characteristics, perceptions, values, beliefs, background, and environment (Krueger and Brazeal, 1994). According to Bonney et al. (2013), entrepreneurship in agriculture refers to the opportunities to create a more efficient and effective agricultural system.

Entrepreneurship and innovation are among the main factors in adopting VA technologies (Coltrain et al., 2000; Womach, 2005). Encouraging agricultural entrepreneurship and innovation has become a priority for policymakers and promoting VA technologies have been a significant focus (Knudson et al., 2004). To illustrate the importance of entrepreneurship and innovation, the USDA created the Value-Added Producer Grant (VAPG) in 2000. Ten Agricultural Innovation Centers were created to promote the benefits of producing and marketing VA products (National Commission on Small Farms, 1998). As a result, agricultural entrepreneurs adopt VA technologies to increase market diversification and their share of the revenues from the sales of agricultural products (Coltrain et al., 2000). According to Bonney et al. (2013), agricultural entrepreneurship creates a more efficient agricultural system by utilizing innovative ways. High levels of entrepreneurship are often related to the good financial health of small farmers due to the premium prices they usually get from their differentiated products (Briscoe and Ward, 2006).

### 2.3 Value-added Technologies in Agriculture

Monchuk et al. (2007) reported that counties with greater reliance on agriculture tend to experience less economic growth than those with less agricultural support, except for counties adopting a more significant share of VA technologies. While farmers adopting VA technologies may face increased risks, they are typically rewarded with higher revenues than farmers not adopting these technologies (Brees, Parcell, and Giddends, 2010). At the farm level, VA technologies tend to increase revenue, and this increase tends to be distributed throughout their communities (Drabenstott and Meeker, 1997; Mkandawire, 2018). Alonso (2011) found that almost a third of the growers he surveyed maximized their profit with VA technologies, turning unmarketable fresh products into differentiated products. Farmers implementing VA technologies can improve local economic growth by creating jobs and linkages developed with other businesses (Monchuk et al., 2007).

Aligning to consumer preferences with VA products motivates farmers to think beyond the goods they produce and analyze the opportunities to be economically feasible by creating value for their consumers. Farmers tend to capitalize on VA technologies opportunities by adopting an activity traditionally done further down the food chain in line with the traditional capture approach to VA agriculture (Brees et al., 2010). For example, instead of selling raw commodities for further processing, farmers can process their products—such as milling wheat into flour, making orange juice from fresh oranges, cutting the produce into ready-to-eat vegetables. They can also deliver services, such as packaging and washing to provide products more easily consumed, closer to the market, or when supplies are lower and prices are higher.

Farmers can integrate the supply chain to create closer relationships between farmers and consumers rather than simply competing for dollars with other farmers in the supply chain. This connection between farmers and consumers can be mutually beneficial. On the one hand, farmers can earn more than wholesale prices. While consumers might pay a premium to obtain what they recognize as higher-quality goods that meet their form and identity preferences, one of which may be a relationship with the farmer. Thus, the approach relies on creating value by cultivating competitive advantages focused on consumer relationships (Brees, Parcell, and Giddens, 2010).

These technologies that create and preserve consumer-preferred characteristics along the food chain include labels and other segregation techniques done at the production stage. For example, organic product identity is obtained through organic practices at the growing phase, can be certified, and can carry a price premium over non-organic products of the same type regardless of the product's distribution channel. Similarly, practices such as segregating non-genetically modified organism (GMO), chemical-free, locally grown, and state-produced can also enable farmers to create additional value by satisfying, managing traceability, and giving assurances related to some customers' preferences for products with a particular identity and quality characteristics (Brees et al., 2010).

### 2.4 The Value-Added Producer Grant (VAPG)

The USDA has been supporting VA technologies through the VAPG, one of the leading programs supporting the adoption of VA technologies in the U.S. This program was established in 2000 as a part of the Agricultural Risk Protection Act of 200 code 231, a crop insurance reform bill. The VAPG was created to enhance the value creation in small farms to increase revenue and support market expansion (National Commission on Small Farms, 1998).

The VAPG provides funding for farmers adopting VA technologies related to VA products' processes and marketing. The program's goal is to encourage new products, create and expand marketing opportunities, and increase farm income. Independent producers, agricultural producers' groups, cooperatives, and majority-controlled producer-based business ventures are the groups eligible to apply for the funds. This program has $76 million available for 2021, with 46% coming from the COVID-19 relief funds. The maximum grant amount is $75,000 for planning activities, including developing feasibility studies and business plans for VA technologies. On the other hand, the maximum amount for working capital is $250,000, which can be used for processing costs, marketing and advertising expenses, and some inventory and salary expenses (USDA, 2021).

Solano et al. (2018) reported that VAPG funds increased the farm survival rate from 33% up to 74% after ten years, and VAPG recipients created more jobs than non-VAPG recipients. Rupasingha et al. (2018) found an employment increase of about 40% for VAPG beneficiaries farmers. These farmers employed five to six more workers than non-recipients in five years after obtaining funds. Farmers' marketing strategies tend to be boosted with VAPG. Anderson et al. (2019) showed the beneficiaries proportional increase in online marketing and sales strategies for their products as time progresses.

## 2.5 Market Access of VA Agricultural Products

Market access is the key explanatory variable in this study. In general, market diversification refers to an increase in the number of markets accessed by the farmer (Kime, 2016). Ruslan et al. (2013) found that market access is a crucial factor influencing the adoption of VA technologies. This study illustrates that farmers tend to follow consumers' demand for VA produce, which tends to adopt VA technologies among growers. Since farmers follow market trends, they tend to tailor their products to the market they are using. For example, a farmer who only sells to farmers' markets might be limited to producing mainly summer crops; however, if that farmer acquires another market channel, the probability that she/he will produce different products can increase.

According to Boland et al. (2009), the information provided by the market was significantly crucial to the VAPG's success. This information determined where and when to consider opportunities to adopt VA technologies. Clark (2020) indicates that the combination of VA technologies and direct marketing, such as selling at farmers' markets, are commonly recommended strategies for increasing income and improving the economic viability of small farms. His research demonstrates the potential of adding value to raw farm products and generate substantial additional income by producing and selling ready-to-eat food. After adopting VA technologies, farm income increased by over 2.5 times compared to income before adopting VA technologies (Clark, 2020).

Grunert et al. (2005) found that market diversification enables better organizational networks, building trust, reducing transaction costs, and driving VA technologies. It is expected that farmers selling to a more significant market outlet will have relationships with more buyers. Hence it can lead to adopting VA technologies to provide a broader range of products to them. Besides, farmers reaching more markets are more likely to adopt food labels as a strategy to convey better information about their products to the consumers (Golan et al., 2001).

## 2.6 Food Labels in The Specialty Crop Industry

The asymmetric information theory can be used to illustrate the proliferation of food labels. This term mainly refers to when one party in a transaction (producer) has more information than the other (consumer) (Akerlof, 1978). To illustrate, consumers may not directly observe the development of food production, handling, and processing, which brings difficulty to transfer this information from farmers to consumers (Messer et al., 2017). These "invisible" attributes desired by consumers increase the distance between the consumer and producer in today's food system, and it represents obstacles for effective communication and the establishment of trust (Sogn et al., 2014). Food labels are commonly used to identify product features and firm characteristics to set this good apart from competing products (Hu et al., 2011).

Food labels allow buyers to protect themselves from risks concerning health or money (i.e., chemical-free labels). Other labels convey information responding to moral concerns, for example, when labels offer information that concerns environmental welfare (i.e., organic labels). Labels can also attempt to respond to consumer (or interest-group) demand to support some demographic characteristics (i.e., locally produced labels). Farmers adopt these labels to convey information related to production and handling practices and differentiate their products (Roe and Sheldon, 2007).

The willingness-to-pay (WTP) appears to be the best approach in theory to capture the gains that farmers receive from food labels (Viscusi, 2018). Researchers have found that consumers are willing to pay for labels used in VA products (Ernst et al., 2008; Hu et al., 2009). Armstrong et al. (2005) found that nearly 65% of their study population would pay a price premium for products with health benefits. Bernard and Bernard (2010) found that consumers would be willing to pay $0.98 more for each pound of chemical-free products. Ernst and Darby (2008) highlighted that local labels capture a consumer premium but that state-level labels significantly influenced consumer preferences. Many studies have found that consumers were willing to pay more per organic label produce (Verhoef, 2005; Hu et al., 2009). For example, Hu et al. (2010) found that consumers were willing to pay $0.25 more per jar of jams made with organic blackberries certified, and the presence of state-produced labels increase by $0.15 for the same jar of jam.

The main drivers to adopt food labels among farmers are economical, idealistic, ethical, demographics characteristics, environmental concerns, and philosophical beliefs (Hartlieb and Jones, 2009; Mzoughi, 2011; Padel, 2001). According to Veldstra et al. (2014), economic drivers tend to be the most critical factors influencing the likelihood of a farmer to adopt labeling strategies. However, several studies have recognized the significance of non-economic motivations, such as concern for the environment, in farmers' decisions to adopt environmentally-friendly technologies as organic certification (Läpple and Van Rensburg, 2011).

This study focuses on farmers' use of labels for VA products such as certified organic, chemical-free, locally grown, and state-produced labels. This reflects that the product was marketed or segregated to enhance its value, leading to these activities being classified as VA technologies. There are several studies in the decision-making process toward VA technologies and food labels in separates contexts. Nevertheless, there is no literature focused on using food labels as the entrepreneurial next step after adopting VA technologies. Based on our data, we aim to understand what drives farmers to adopt these different labels as VA technologies and explain the factors driving this entrepreneurial marketing step.

## 2.7 Drivers and Barriers of Adopting Value-Added Technologies

Gender plays an essential role in the adoption of VA technologies. As men generally focus on production activities, women are more likely to adopt new farming technologies, take more risks than men, and present themselves as innovators (Seuneke and Bock, 2015). Education is an essential factor in the technology adoption literature (Hall, 2005). According to Mishra et al.

(2009), better educated and trained farmers were found to have a better financial performance in new farm businesses engaging in VA agriculture.

Access to funding is a significant factor influencing the adoption of VA technologies. According to Batterink et al. (2010), affordable and safe financing sources encourage innovation and help the agriculture sector grow. Government support has been found to help the adoption of VA technologies. Ruslan et al. (2013) found that producers want the government to support VA agriculture with better facilities, financial support, and enforcement. To illustrate, programs like the VAPG mentioned before have significantly increased the adoption of VA technologies among specialty crops farmers.

Social networks are characterized by individual members and links in information, money, goods, or services flow (Maertens and Barrett, 2012). Given this definition, we framed networks as family farmers, friend farmers, and farmers in the community. Lately, the economic literature has noted the importance of social networks in the technology adoption process. Maertens and Barrett (2012) found that having social interactions with farmers who have adopted technological innovations tends to increase the likelihood of adopting those technologies from 20 to 50%. Ward and Pede (2015) showed that network effects could be significant in the technology adoption process than Extension agents in agriculture. However, according to Lewis (2002), Extension agents help promote the adoption process in VA technologies. She found that farmers who had a stronger relationship with Extension educators were considering adopting technologies to improve their farm income.

Farmers' perceptions play an essential role in the technology adoption process in agriculture (Krueger and Brazeal, 1994). Camenisch (2013) researched the producers' satisfaction with adopting VA technologies. Her results showed that most of the farmers considered raw products more successful than their VA products. However, these farmers stated that their profits increased due to the sale of these VA products. This study shows that perceptions like satisfaction or success can be measured in various ways, not necessarily in economic terms.

The literature has reported barriers deterring growers from adopting VA technologies. Camenisch (2013) conducted a study about barriers to adopt VA technologies; her results showed that lack of knowledge, time, funding, sources of information, and entrepreneurial skills were the most critical barriers to adopt VA. This study illustrated how the lack of resources was one of the main barriers that farmers had to surpass to adopt VA technologies. This specific issue is relevant because most farmers adopting VA have small farming operations with limited financial resources. Besides, farming in the middle can become a barrier to adopt new technologies. According to Stevenson et al. (2014), medium-sized farmers have been experiencing a downturn in productivity due to lack of government policy, changes in the agriculture industry to large-scale farming, and centralization of agricultural capital. Medium farmers face a market access gap; these farms are often too small to the high demands of the retail sector, and they sometimes are too large for direct-to-consumer market channels (Stevenson et al., 2014).

Clark (2020) reported that material and labor costs associated with VA technologies were deterrent factors in the adoption process of these technologies. The need for skilled workers in these operations highly increases labor costs. The lack of knowledge and training are the most significant barriers to education and information (Rodriguez et al., 2008). The lack of institutional support and sources of information are substantial variables deterring the adoption of technologies.

Farm location has been shown to influence the decision to adopt VA technologies. Torres and Marshall (2018) found that farm location was a significant variable in farmers' decision to decertify organic. They reported that higher populated areas that offer access to better markets are essential factors in the technology adoption process. Farms located in the Northeast states were more likely to adopt organic practices since organic agriculture tends to concentrate in areas where the demand and processing, and distribution chains exist (Dimitri and Oberholtzer, 2009). In contrast, the lack of urban markets in the Midwest might not incentivize farmers to adopt new technologies such as organic certification (Torres et al., 2016).

In summary, this literature review explores past research on VA technologies. After revising the most important factors related to this technology adoption process, we propose an econometric model that fits with the previous studies in this area. This section shows that research regarding VA technologies is becoming more relevant as the benefits from these technologies are discovered. However, past research lacks an integrated model of adopting VA technologies with food labels in the specialty crop industry, which is the gap that this study intends to fill.

# CHAPTER 3. DATA AND METHODOLOGY

## 3.1 Data Description

Data for this study came from a 2019 web-based survey of specialty crop growers who were part of email lists of grower associations and the Food Industry MarketMaker database. The lists compiled 3,557 email addresses of growers located in 32 states.[1] The list of growers was screened to eliminate duplicate entries and operations. These databases facilitated producers' access to growing fruits, vegetables, and herbs (i.e., specialty crops). Our data included farmers selling in direct-to-consumer (DTC) market channels, intermediate markets, and wholesale outlets. DTC markets are those where the farmer sells directly to consumers, such as farmers' markets, while intermediate markets are those where the farmer sells to local restaurants or retailers (Torres et al., 2016). Lastly, wholesale outlets are those where the farmer sells to processors, distributors, and wholesalers (Woods et al., 2013).

The web-based survey was conducted using a mixed-mode design using Qualtrics software. To increase the participation rate, we included an incentive of a ten-dollar gift card to the first thousand farmers who completed the survey. Dillman et al. (2014) noted that including token incentives tends to increase online survey participation. We sent three email reminders with intervals of two weeks between March and April 2019. A total of 766 farmers completed the survey, for a response rate of 21.5%, which is considered an acceptable rate for this type of survey (Dillman et al., 2014). The survey letter is attached in Appendix B.

[1] Alabama, Arizona, Arkansas, California, Colorado, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Montana, New Mexico, New York, North Carolina, North Dakota, Oklahoma, Oregon, Rhode Island, Tennessee, Virginia, West Virginia, Wisconsin, and Wyoming.

The questionnaire included questions related to farmer's demographics (i.e., educational attainment, gender, farming experience), farm characteristics (i.e., crops, markets, and growing technologies), and farmer's network perceptions towards their farm. The Institutional Review Board approved the questionnaire for compliance with ethical standards for human subjects.

The subsample for this study included 581 operations growing fruits, vegetables, and culinary herbs. Farmers who did not respond to the questions regarding VA technologies were excluded from the study. We followed the USDA VA Producer Grant (VAPG) (USDA-AMR, 2015) to categorize farmers into two groups according to their adoption of VA technologies used in 2018. The first farmer category, *no VA*, encompasses operations that did not use any VA technology in 2018. The second group, *VA*, is for farmers that produced VA products such as dried or dehydrated produce, cut produce into customer-ready portions, and washed produce. From the sample of 558 farmers, 265 (47.5%) were categorized as *no VA*, and 293 farmers (52.5%) produced and sold VA agricultural products. All analyses were conducted using Stata (release 15; StataCorp, College Station, TX). We made multiple comparisons among means in analyzing variance (ANOVA) models using Tukey's honest significant test at the 10% significance level. We considered farmer type for means comparisons across columns.

### 3.2 Empirical Model Specification

In the following section, we explain the econometric models used in this study. Using a standard probit, our primary goal is to investigate how market access influences the adoption of VA technologies in section 3.2.1. Also, we address the potential simultaneous causality that may arise from the relationship between the adoption of VA technologies (vertical diversification) and the number of crops grown by a farmer (horizontal diversification), as these two types of agricultural diversification can be commonly adopted by specialty crop growers (Barbieri and

Mahoney, 2009). While we propose that crop diversity may influence farmers to adopt processing technologies that add value to their agricultural products, lower risk, and increase revenue, one may argue that the adoption of VA technologies increases the likelihood to produce more crops to take advantage of the technological investment. Similarly to Ahmadzai (2017), we used an instrumental variable (IV) approach to control the possible endogeneity from unobserved characteristics that may lead a farmer to adopt VA technologies in section 3.2.2.

We also addressed the use of food labels that may be part of the VA technology adoption. In other words, we want to look at how farmers may be taking a step forward by using labels to convey their stories after adding value to their products. We expect that the selection of market channels can motivate farmers to use food labels to differentiate themselves while adding value to their crops. For example, farmers adding value to their products and selling them locally may be more likely to label their VA products when compared to those selling the VA produce to wholesalers and processors. Thus, we took a step forward from the VA literature to investigate what drives farmers to VA technologies and use food labels. We redefined our dependent variable, and the categorization is explained in section *3.2.3*. We used multinomial probit regression and ordered probit regression to model the decision-making process of adopting VA technologies and food labels.

### 3.2.1 Baseline Setup: A Probit Model of the Decision to Adopt VA Technologies

A standard probit regression model was used to estimate how the choice of market channel drives the decision to adopt VA technologies:

$$Y_i^* = \Phi\,(\beta_0 + market_{1i}\beta_1 + X_{2i}\beta_2), \qquad (1)$$

where the dependent variable $Y$ was the binary decision to adopt VA technologies. Farmers were grouped into two categories: those who used VA technologies in their specialty crop operation in

2018 (*VA)* and those who did not use any VA technologies (*no VA)*. Thus, the dependent variable has the value $Y = 1$ if the farmer self-reported the adoption of VA technologies (e.g., drying or dehydrating produce, cut produce into customer-ready portions, and wash produce), and $Y = 0$ otherwise.

Similar to Torres et al. (2016) and Aggarwal et al. (2018), we propose that market diversification can drive the adoption of new practices, such as VA technologies. Social interactions and market relationships, especially those developed at local markets, may provide farmers with feedback and price premiums and motivate them to differentiate their products by adding value to specialty crops. Our hypothesis is that farmer's decisions regarding market access may affect the adoption of VA technologies. The key explanatory variable (*market access)* is decomposed into two components: number of sales methods used (first bracket) and distribution of sales per method (second bracket):

$$market\ access\ = \left(1 - \frac{1}{methods}\right) + \sum_i \left(\frac{1}{methods^2} - \ share_i^2\right) \qquad (2)$$

The first bracket in Eq. (2) accounts for the number of sales methods (*market diversification index*) used by the farmer, including farm stands, farmers' association, Community Supported Agriculture (CSA), farmers markets, food hubs, grocery stores, internet orders, processors, restaurants, school districts, wholesalers, and other markets. Following Eq. (2), the *market diversification index* increases as the number of methods of sales used increases. For example, a grower using five market outlets would have a value of 0.8 for the first bracket, while a farmer selling only through a farmers' market (one market outlet) would have a value of zero. In other words, a higher number of selling methods used by the farmer illustrates a higher degree of market diversification.

The second bracket in Eq. (2) illustrates the market access in the distribution of sales methods (*market distribution index*), representing the proportion of sales through market outlets. For example, a farmer that reported selling his/her crops in the same proportion (50/50) between farmers' market and wholesale sales would have a distribution component of $-0.25$ or $\frac{1}{2^2} - (0.5^2 + 0.5^2) = -0.25$. However, a producer who sells 90% of products through farmers' markets and only 10% via wholesale would have a diversification component of $\frac{1}{2^2} - (0.9^2 + 0.1^2) = -0.57$. In other words, a higher negative number of the diversification component would indicate an unequal distribution of sales.

Table 1 describes the explanatory variables represented in the set of covariates $X_{2i}$ in Eq. (1). The parameter vector $\beta = (\beta_0, \beta_1', \beta_2{}')'$ was estimated, and $\Phi(\cdot)$ is the standard normal probability distribution function. This empirical model fitted into the scope of regressions that model the decision-making process of farmers adding value to their produce. Identification of the factors that influenced the decision to use VA technologies comes from several sources. The set of covariates $X_{2i}$ contain significant drivers of adopting VA technologies such as farmer demographics, farm characteristics, farmer attitudes, and network and information variables.

Farmer demographics included educational attainment, gender, race, if respondent farms part-time, and farming experience (in years). Farm characteristics included the number of crops produced, number of family members working at the farm, number of employees hired (permanent and temporary), total owned and rented land, the legal structure of the farm, percentage of the farm income that comes from specialty crops. We followed the USDA Economic Research Service categorization of family farms to base sales cutoff for the farm size category. Small size operations were those reporting gross sales from \$5,000-\$99,999, medium farms reported from \$100,000-\$250,000, and large operations were the ones reporting more than \$250,000 in 2018 (USD-ERS, 2020). Farmers were also asked if they perceived sales and the number of employees grew from 2018 to 2019. Following the U.S. Census Bureau, we compared farmers from the Midwest with the rest of the country. The Midwest region grouped farms located in Illinois, Indiana, Iowa, Michigan, Minnesota, North Dakota, and Wisconsin.

The farmer's response of the network variable was defined if family, friends, and farmers in the community have adopted VA technologies. Valuable sources of information included information obtained from industry, other farmers, and Extension personnel. Attitudinal questions were used to examine farmer's perceptions of agriculture and VA technologies. Likert-like scales were chosen to capture respondents' perceptions because they tend to be easy for individuals to answer in a survey and produce good results (Lusk and Coble, 2005). The producer's perceptions of agriculture and their business's profitability were rated on a five-point Likert-like scale from strongly disagree (1) to strongly agree (5). Perception variables included if farmers agreed that farmers should receive government support to add value to produce. Farmers should receive financial assistance to accommodate the changing regulatory landscape. We also asked farmers if they were satisfied with their farm business, they had a positive experience trying new farming technologies to increase the profits, and it was hard to find reliable customers for VA produce.

### 3.2.2 Addressing Endogeneity

The regressor used in Eq. (1) raised the concern of endogeneity from a possible bias caused by simultaneous causality between the adoption of VA technologies and the number of crops produced. Simultaneous causality occurs when the causality may occur in both directions: from the regressors or independent variables to the dependent variable and from the dependent variable to the regressors (Bascle, 2008). Ignoring potential endogeneity can lead to endogeneity bias and, consequently, result in the inconsistent effects of crop diversification on the adoption of VA technologies (Bascle, 2008). Endogeneity may be caused by the relationship between adopting VA technologies (vertical diversification) and diversifying crop mix (horizontal diversification). For example, one can assume the farmer's decision to increase their crop mix might be driven by an investment in a dryer (i.e., VA technology). Farmers may want to increase the return on investment of these technologies by adding to the number of crops grown, dried, and sold. On the other hand, farmers who grow a large number of crops may want to take advantage of their wide variety of products; thus, they can be more likely to adopt VA as a strategy to increase their farm income and decrease their loss of production. We proposed that the number of crops produced on the farm influences the decision to adopt VA technologies. We developed a two-stage probit approach with endogenous regressors to address the possibility of endogeneity. Using an IV approach, we aim to find a variable that influences the potential endogenous regressor (*number of crops)* but is not related to the farmer's decision to adopt VA technologies.

We proposed the use of *farming technologies* (e.g., artificial lighting, aeroponics, aquaponics, hoop houses, hydroponics, greenhouses, plasticulture, and irrigation) as the instrument for the variable *number of crops*. According to the diversification literature, farmers using farming technologies tend to have, on average, six additional crops in their crop mix (Lancaster and Torres, 2019). The use of these farming technologies can help farmers extend the farming season, increase yield, and improve pest management, which tends to influence the adoption of a higher number of crops in their operations (Carey et al., 2009). This IV captures the effect of the potential endogenous regressor (*number of crops)* on the dependent variable (*VA*) by influencing just the potential endogenous and not influencing the dependent variable. In other words, the IV influences the potential endogenous regressor but not the dependent variable.

We considered the following two-stage model, in which $Y_{1i}^*$ is the dependent variable in Eq. (3) ($Y = 1$ if farmer self-reported the adoption of VA technologies and $Y = 0$ otherwise), and $Y_{2i}$ is the potentially endogenous regressor in the equation $(number\ of\ crops)\ in\ Eq. (4)$. The variable $Y_{1i}^*$ in Eq. (3) is latent and hence is not directly observed. Instead, the binary outcome $Y_1$ is observed, with $Y_1 = 1$ if $Y_1^* > 0$, and $Y_1 = 0$ if $Y_1^* \leq 0$. The equation of primary interest is Eq. (3), while Eq. (4) is called first-stage or reduced-form equation, that is,

$$Y_{1i}^* = \beta ncrops + X_{1i}\gamma + u_i \quad \text{(3)(Structural equation)}$$

$$Y_{2i} = X_{1i}\pi_1 + IV\pi_2 + v_i \quad \text{(4) (Reduced-form)}$$

where $i$ = 1,…, $N$; $X_1$ is a $K_1$ x 1 vector of exogenous regressors, and $IV$ is the instrumental variable (*farming technologies*) that affects $Y_2$, but can be excluded from Eq. (3) because it does not directly affect $Y_1$; however, this is debatable (Cameron and Trivedi, 2009). In Table 3, the first-stage Eq. (4) was modeled as an ordinary least square (OLS) to explain the variation of the potentially endogenous variable (*number of crops*) as a function of *farming technologies* and exogenous variables. Thus, the first-stage equation was used to identify the strength and validity of *farming technologies*. The two-stage model is an alternative estimation procedure with normal errors (Newey, 1987) that uses a minimum chi-squared estimator ($\mathcal{X}^2$ test). This estimator also assumes multivariate normality and homoscedasticity.

### 3.2.3 Modeling the Adoption of VA Technologies

According to Asfaw et al. (2015), producers tend to adopt more than a single technology in their operations. Empirical technology adoption theory has noted that farmers usually consider a set of possible technologies and choose the technology bundle that maximizes their profitability (Teklewold et al., 2012). This theory indicates that the adoption decision is inherently multivariate, and seeking a univariate model would ignore useful, valuable economic information about the interdependent nature of a farmer's decision-making (Dorfman, 1996).

We broaden our definition of diversification to include food labels and investigate how market access influences this adoption among VA farmers. Thus, our study took a step forward from the VA literature to investigate the drivers of using food labels for VA agricultural products (i.e., labels about organic certification, chemical-free, local grown, and state-produced) and how market access influences the decision to adopt these technologies. The dependent variable changed from a binary ($Y = 1$ if farmer self-reported the adoption of VA technologies, and $Y = 0$ otherwise) to a categorical variable. Farmers were categorized into three groups to reflect the farmer's decision to adopt VA technologies with or without food labels. The first group was farmers who decided not to adopt VA technologies ($Y = 0$). The second group was farmers who adopted VA technologies (e.g., drying or dehydrated produce, cut produce into customer-ready portions, and wash produce) ($Y = 1$). The third group was composed of farmers who added value to their products and used food labels to increase the differentiation of those procedures (e.g., organic certification, chemical-free, local grown, and state-produced) ($Y = 2$).

We used multinomial probit regression and ordered probit regression to model the decision to add value and the use of food labels illustrated in Eq (5):

$$Y_i^* = \Phi\,(\beta_0 + market\beta_{1i} + X_{2i}\beta_2 + \varepsilon_i), \quad i = 1,2,\dots,N \qquad (5)$$

Using two econometric models, this study sheds light on farmers' decision-making to adopt VA technologies and food labels. The difference between an ordered (ordered probit) and a random decision-making process (multinomial probit) has important implications for the adoption and success of these technologies. For example, if the ordered probit explains better the data, we would infer that critical drivers in the adoption would lead farmers to keep advancing in the VA chain.

On the other hand, if the multivariate would fit better the data, it might tell us that farmers can go from no adopting VA to adopt VA with food labels in one single step. Akaike information criterion (AIC) (Akaike, 1974) and Bayesian information criterion (BIC) (Neath et al., 2012) were used as techniques for the selection of fit between the models (multinomial and ordered probit). The following equations were used to estimate the AIC and BIC indicator:

$$AIC = -2 * ln(L) + 2 * k \qquad (6)$$

$$BIC = -2 * ln(L) + 2 * ln(N) * k \qquad (7)$$

where $L$ is the value of the likelihood, $N$ is the number of recorded measurements, and $k$ is the number of estimated parameters. Since both regressions provide log-likelihood values, a likelihood ratio test was also used to compare the two models:

$$LR = -2\ln\left(\frac{L(m_1)}{L(m_2)}\right)$$

where $L$ is the value of the likelihood of each of the regressions.

#### ***3.2.3.1. Multinomial Probit Regression***

The multinomial probit model measured the influence of market access on the decision to adopt VA technologies and food labels. This model provided a flexible approach to measure the effect of the explanatory variable on each step of the technology adoption process because it does not enforce restrictive assumptions (Hermann, 2013). In this model, we proposed that farmers can choose from not adopting VA technologies to adopting VA technologies and using food labels to market VA products. The process does not follow a natural order.

Following Cameron and Trivedi (2009), the multinomial probit model was based on the latent categorical variable used in Eq. (5), where the dependent variable $Y_i$ was the categorical decision to adopt VA technologies and food labels:

$$Y_{ij}^{*} = \Phi\left(\beta_0 + market\beta_{1ij} + X_{2ij}\beta_2 + \ \varepsilon_{ij}\right), \quad i = 1,2, \dots, N \quad (8)$$

the key vector of explanatory variables (*market*) and the other set of covariates was the same as in Eq. (1), and Φ was the standard normal cumulative distribution function, and $\beta = (\beta 0, \beta 1, \beta 2\ )$ is the vector of unknown constants. In this model, the baseline category was the group of farmers who did not adopt VA technologies. The $J$ vectors of regression coefficients $\beta_{1i}\ and\ \beta_{2i}$ were linked with the coefficient $\beta_0$. The $\varepsilon_i, 1, \dots, \varepsilon_{ij}$ were distributed independently and identically standard normal. Thus, the probability that observation *i* will select alternative *j* is:

$$P_{ij} = P(Y_i = j) = \Phi\ (X'_{ij}\beta)$$

### *3.2.3.2. Ordered Probit Regression*

We also used an ordered probit regression to estimate the factors influencing the adoption of VA technologies and food labels. The ordered probit is an appropriate framework to model ordinal survey responses where the observed dependent variable has an ordinal scale (Greene, 2003). Under this model, we considered that the producer's decision-making towards adopting VA technologies has an ordered process. The dependent variable is a series of three steps or categories with logical starting and ending points (Fullerton 2009). In other words, the farmers' starting point is not to adopt VA technologies. After that, farmers' first step toward VA technologies is to dry or dehydrated produce, cut produce into customer-ready portions, and wash produce. Once they adopted the prior VA technologies, farmers decide to use food labels (e.g., organic certified, chemical-free, locally-grown, and state-produced) to differentiate their products.

This model is based on the latent categorical variable used in Eq. (5). This variable is a linear combination of some observables $X_{2i}$ and a disturbance term ε with a normal distribution.

In particular, letting $i$ = 1, 2, $n$ index the business, and for the case in which there are three ordered outcomes (e.g., $Y_i$[0, 1, and 2]) which are the same as in Eq. (8):

$$Y_i^* = market\beta_{1i} + X_{2i}\beta_2 + \varepsilon_i \quad (9)$$

in which $Y_i^*$ is the unobserved latent variable and $Y_i$ is the observed ordinal variable:

$$Y_i = 0 \; if \; Y_i^* \leq 0 Y_i = 1 \; if \; 0 < Y_i^* \leq \mu_1 Y_i = 2 \; if \mu_1 < Y_i^*$$

We expressed the cumulative probabilities as:

$$\Pr(Y_i = 0 \mid X_i = x) = \Phi\,(-X_i\beta) \; \Pr(Y_i = 1 \mid X_i = x)$$

$$= \Phi(\mu_1 - X_i\beta) - \Phi\,(-X_i\beta) \; \Pr(Y_i = 2 \mid X_i = x) = 1 - \Phi(\mu_1 - X_i\beta)$$

where $\Phi\,(.)$ is the standard normal cumulative distribution function.

# CHAPTER 4. EMPIRICAL RESULTS

## 4.1 Summary Statistics

Table 2 shows the description of the explanatory variables with mean differences for all the variables used in the models by farmer. The first bracket of the *market access* equation, the *market diversification index*, is significantly higher for VA farmers (0.52) when compared to the index for farmers that do not adopt VA technologies (0.33) ($P < 0.01$). These results are similar to Veldstra et al. (2014), who reported that farmers adding value through organic production tend to sell their produce through more market channels. In other words, VA farmers sell their produce to more markets.

Women farmers represent a third of the total sample data, which matches the 1.2 million female producers accounting for 36% of the country's 3.4 million producers reported in the 2017 Agriculture Census (USDA-NASS,2020). In fact, 38% of the VA farmers are women, which is significantly higher than the 26% of female farmers in the non-VA group ($P < 0.05$). An explanation can be that a more significant proportion of female farmers adopt VA technologies, while men tend to focus on increasing yield (Dias et al., 2019). On average, farmers adopting VA technologies grow more than twice the number of crops (20) than those not adding value to their crops (8) ($P < 0.01$). These results are consistent with De Benedictis et al. (2009), who found that operations tend to become more diversified as they move out of early development stages; in this case, when operations start to adopt diversification strategies. Unsurprisingly, over 37% of part-time farmers do not adopt VA technologies, significantly higher than the 29% for VA farmers ($P < 0.05$). According to Jablonski et al. (2020), agricultural operations adding value to their products tend to be more labor-intensive than their counterparts and may demand farmers to find the commitment to farm full-time.

Although there is no significant difference across farm types regarding the number of employees or family working at the farm, farmers adopting VA technologies, on average, reported higher employment growth in their operations (17%) in 2018 than non-VA farmers (12%) ($P$ < 0.1). Similarly, farmers adopting VA technologies reported, on average, more growth in sales (37%) in 2018 than their counterparts did (30%) ($P$ < 0.1). These results illustrate how farmers adopting VA technologies tend to experience more economic growth than their counterparts.

Maertens and Barrett (2013) highlighted the importance of networks on agricultural technology adoption. Our findings report that 37% of farmers who adopted VA technologies have at least one member of their community (e.g., family, friends, or farmers) that have adopted VA technologies. This value is significantly lower for the farmers who did not adopt VA ($P$ < 0.01). Interestingly, across all sources of information analyzed (industry, farmers, and university Extension), only those coming from industry stakeholders such as industry associations are significantly different for VA farmers. Almost three-fourths of farmers without VA technologies consider industry associations as useful source of information; conversely, 65% of their counterparts report this useful source of information ($P$ < 0.05).

We find that all the perceptions of VA technologies evaluated in our model are statistically different. More farmers adding value to their produce perceived they should receive government support to add value to their crops ($P$ < 0.1) and financial assistance to be able to accommodate the changing regulatory landscape than non-VA operations ($P$ < 0.05). VA farmers reported a positive experience with VA technologies to increase profits ($P$ < 0.01) and declared that it was harder to find reliable customers for VA produce ($P$ < 0.01) than non-VA farmers. In contrast, farmers without VA technologies are significantly more satisfied with their farm business than those adding value to crops ($P$ < 0.05).

## 4.2 Regressions Results

In the following section, we show the results of the econometric models performed in this study. First, we explain the findings of the standard probit regression to show the influence of market access in the farmers' decision to adopt VA technologies. We then show the two-step instrumental variable probit regression results to tackle the potential endogeneity issue raised by the relationship between vertical (VA technologies) and horizontal diversification (number of crops). Lastly, we incorporate food labels for VA produce as the following farmers' step into the VA chain. We present the results from the multinomial and ordered regressions and assess their goodness of fit. We aim to understand whether farmers' decision-making process is carried out in a random (multinomial probit) or ordered (ordered probit) manner.

### 4.2.1 Standard Probit and IV Probit

This study provides empirical evidence of the effect of market access and key drivers in farmers' decision-making process towards VA technologies. This section shows the result from the standard probit regression and the two-step instrumental variable probit. Table 3 displays the first stage (reduced form) of the IV probit regression measuring the impact of using *farming technologies* as an IV on the *number of crops* (endogenous variable) from Eq. (4). Table 4 reports the coefficients and standard errors from the standard probit and the IV probit regressions. The results from instrumental IV are consistent with the standard probit. We find that standard errors and robust standard errors are similar, suggesting the lack of heteroskedasticity in our data (King and Roberts, 2015).

Results from Table 3 are aimed to provide the validity of our IV. The statistically significant results and the strong correlation between *farming technologies* (IV) and the *number of crops* (potential endogenous variable) in Table 3 illustrate the strength and power of the IV used in this model. Consistent with Lancaster and Torres (2019), we found farming technologies were a major factor influencing crop diversification among specialty crop operations, demonstrating the relevance of the IV. Results from Table 3 appear in the Appendix A section.

A key finding of this section is that in the instrumental variable probit, the parameter *p* from the Wald test of exogeneity is not statistically significant ($P = 0.36$) (Table 4). A *p* that is not statistically significant is telling us that *number of crops* is unlikely to be endogenous. Thus, there is not sufficient evidence for declining the null hypothesis that the model is exogenous. In other words, endogeneity is not likely to be an issue in the analysis, and the results from the standard probit can be used to explain how market access and other factors influence the decision to adopt VA technologies among specialty crops operations. These findings also show us that the number of crops produced by farmers is a crucial factor influencing the adoption of VA technologies and not the other way around.

Results from Table 4 provide robust empirical evidence that the first component (*market diversification index)* of our critical explanatory variable equation (*market access*) significantly influences the farmer's decision to adopt VA technologies. On average, the probability of adopting VA technologies significantly increases by %28.7 as the *market diversification index* increases ($P < 0.01$). This result suggests that the number of markets accessed is a significant factor determining the adoption of VA technologies. One explanation can be that farmers accessing more market channels have a better understanding of consumer trends and demand; thus, they are more likely to adopt VA technologies to differentiate their products. We can infer the importance of accessing a variety of markets and its effect on determining agricultural products. Farmers in remote areas with less market access may not be driven to add value to their produce through VA technologies, and VA policies may not be efficient. On the other hand, policymakers can use these findings to consider those market access policies and incentives to go hand in hand with VA technologies.

Results from the standard probit regression illustrate that the number of crops grown by each farmer is a significant driver of the adoption of VA technologies. Increasing the crop mix by one crop will increase the likelihood to adopt VA technologies by 1.1% ($P < 0.01$). It seems that horizontal diversification has a significantly positive effect on vertical diversification (VA technologies). Our results are similar to Morris et al. (2017), who found that crop diversification has a high impact on technology adoption. Our results suggest that more diversified operations are more likely to take extra steps into the food value chain and add value to differentiate their products (De Benedictis et al., 2009).

Farmers selling only to DTC markets are 9.9% more likely to adopt VA technologies ($P < 0.1$). It may be that local markets provide farmers with social interactions, representing a source of information to tailor products and access price premiums for value-added products. While Low et al. (2020) found that employment is not significant when adding value to agricultural products, Deogharia (2018) reported that farmers adopting VA technologies tend to hire more labor. Our results suggest that labor is a significant driver for VA agriculture in the specialty crops industry. First, family labor plays an essential role in the adoption process of VA technologies. Results from Table 4 suggest that having one more family labor involved in agricultural operations increases the likelihood of the farmer adopting VA technologies by 3.2% ($P < 0.01$). For our sample of farmers, it seems that the family's participation in the agricultural operation positively influences adopting value-added technologies. Second, Table 4 illustrates that farms experiencing employment growth in the previous year increase 13.1% likelihood of adopting VA technologies ($P < 0.05$). According to Jablonsky et al. (2020), agricultural operations adding value to their products tend to be more labor-intensive than their counterparts, explaining the employment growth influence on farmers' VA technologies adoption.

The effects of networks are significant in the technology adoption process (Maertens and Barret, 2013). Results from the standard probit indicate that having a family member, friends, and farmers in the community who have adopted VA technologies increases the probability of VA technology adoption by 13.7% ($P < 0.01$). Our result is consistent with studies reporting the paramount importance of networks in the technology adoption process (Ward and Pede, 2014). Farmers that agreed that it is hard to find reliable customers for VA produce are 12.5% more likely to adopt VA technology ($P < 0.01$). Since farmers adopting VA are looking for markets for their VA products, it is expected that they perceive these difficulties.

### 4.2.2 Modeling the Adoption of VA technologies and Food Labels

In this section, we introduce the use of food labels for VA produce as the next step in the farmer's process of adopting VA technologies. The dependent variable includes a third group of farmers who adopted food labels for their VA produce. The key explanatory variable is the *market access* vector, which is the same as the previous model. We aim to measure the effect of the key explanatory variable in the adoption of VA technologies and food labels for specialty crop operations. Since we want to provide the model that best explains the farmers' decision-making process towards adopting VA technologies, we ran multinomial and ordered probit regressions to address this question.

Table 5 displays the results and the marginal effects of the multinomial and ordered probit models. The $p$-value for the LR test is .177975, which is not significant at $p < .10$. Results from the likelihood ratio test tell us that there is no significant difference among the goodness-of-fit among the two multinomial regressions. Nevertheless, lower AIC and BIC values from the ordered probit indicate better goodness-of-fit when compared to the multinomial probit. These results suggest that the decision-making process in adopting VA technologies is better explained as an ordered process. In other words, it seems that farmers first adopt VA technologies and then add labels to their VA products. Thus, we discuss the results from the ordered probit in the following section. This section shows how the most significant drivers for the standard probit remain critical factors in the use of labels for VA produce. *Market diversification index*, farm characteristics, networks, and perceptions are key factors influencing the decision to adopt VA technologies with food labels.

Our results illustrate that increasing the *market diversification index* will increase the probability of adopting VA technology with food labels by 22.4% ($P < 0.01$). In other words, the higher the number of market outlets used by a farmer, the higher the likelihood to adopt VA and labels. A consumer going to the supermarket might have different preferences than one going to the farmers' market. That is why farmers selling their products through more market channels may better understand consumer demand and use labels to differentiate their products and cater to niche markets. To keep up with new consumer trends, farmers may add value via the processing and labeling of their products.

Similar to the standard probit results, crop diversification increases the probability of adopting VA technologies and food labels. Increasing the crop mix by one crop will increase the likelihood of using labels for VA products by 0.7% ($P < 0.01$). Consistent with Morris et al. (2017), farmers with high levels of crop diversification are more likely to engage in technology adoption. An explanation may be that farmers adopting horizontal diversification techniques (i.e., increasing their crop mix) present more entrepreneurial traits to diversify their production and selling strategies. One can argue that farmers with a high number of crops produced may have to find innovative ways to market their products to maximize the profitability of their operations.

Employment growth seems to be a significant factor influencing the adoption of VA technologies and food labels. Our results illustrate that farmers experiencing an increase in the number of employees between 2017 and 2018 were 7.2% more likely to adopt VA technologies with food labels ($P < 0.05$). Similarly, for each additional family member working on the farm, the likelihood of adopting VA technologies in specialty crops operation increases by 1.9% ($P < 0.05$). Our results are consistent with Edobor et al. (2021), who found that family plays a crucial role in agriculture. Consistent with Jablonski et al. (2020), these results confirm that farms adopting VA technologies and food labels have more labor needs and may benefit from access to competent labor.

Networks that have adopted VA technologies influenced farmers' decisions to adopt VA technologies and use food labels. For instance, having support networks with experience in VA technologies increases the likelihood of adopting VA technologies with food labels by 9.3% ($P < 0.01$). Our results are similar to Maertens and Barrett (2013), who found that the effects of networks play an essential role in the technology adoption process. As expected, perceptions were vital factors in the process of the adoption of VA technologies. Famers having difficulties finding reliable customers for their VA produce are 9.5% more likely to adopt VA technologies and food labels ($P < 0.01$). We expect that having difficulties finding reliable customers may encourage these farmers to add value via processing and label their agricultural products. It appears that the absence of many large, populated areas in the Midwest, compared with the rest of the country, deters farmers from adopting VA technologies and food labels. Farmers from the Midwest are 5.3% less likely to adopt VA technologies ($P < 0.1$). These results are similar to Torres and Marshall

(2017), who found that farmers located in the Midwest are less likely to differentiate themselves through organic production.

Farm size (measured by annual sales) is an essential factor in farmers' decision to adopt VA technologies. Compared to small farms, medium farmers are significantly less likely to adopt VA technologies and food labels ($P < 0.05$). These results keep showing the difficulties of farming in the middle. Medium-sized farmers may find it hard to adopt VA technologies due to the lack of market access. On the one hand, wholesale markets prefer to deal with large farms to reduce their supply chain costs. It is cost-effective to buy 50,000 tomato pounds from one farmer than to buy 5,000 pounds from 100 farmers. On the other hand, middle farmers can find difficult to sell in farmers market because they are too large or do not produce crops that can be sold direct-to-consumers (Kirschenmann et al.,2008; Stevenson et al., 2014).

# CHAPTER 5. CONCLUSION

Ever since the U.S. government began to encourage the use of value-added technologies in 2000 through the Value-added Producer Grant, researchers, Extension agents, and industry stakeholders have supported the adoption of these technologies to improve agricultural productivity, innovations, and entrepreneurship. Although the positive impacts of these technologies have been proven at the county and regional levels, not enough research has been conducted at the farm level. As a result, it was unclear what factors drive and deter farmers from adopting value-added technologies in the U.S. specialty crop industry. This paper aims to provide a better understanding of the agriculture innovation paradox proposed by Cierra and Maloney (2017) ("*why, if returns to the adoption of new technologies are so high, so few farmers adopt them?"*). Our findings show that factors such as market, gender, labor, number of crops, and networks motivate farmers to adopt value-added technologies. In contrast, factors such as farm location, perceptions, and farm size deter them from producing value-added produce. Promoting these drivers and reducing the main barriers to adopt value-added technologies can be essential in designing and delivering initiatives that support the adoption of these technologies.

The first component of our *market access* vector shed light on the importance of market diversification in value-added agriculture. We propose that farmers with greater market diversification might better understand market trends and decide to adopt value-added technologies to tailor their raw products to meet consumer demand. For example, farmers who have close relationships with end consumers at local markets may be more likely to gather the attributes, presentations, and forms of value-added produce that meet their needs. The fact suggests that farmers using direct-to-consumer market channels were more likely to adopt value-added technologies. Obtaining a higher share of consumers' dollars may allow farmers to invest in technologies that differentiate their products and add value to the farmer-consumer relationship.

We can infer that the market is giving signals to farmers that encourage them to adopt value-added technologies. Hence, we may conclude that there is an increased consumer demand for value-added products. These results have clear policy implications. Policymakers should double their efforts to promote programs for new market opportunities. Our results show the importance of developing programs to increase market access, such as the *Market Access Program*, the *Local Agriculture Market Program* (Farmers' Market and Local Food Promotion Program), and the *Specialty Crop Block Grant Program* (SCBGP). Besides, Extension programs should consider market education strategies to support farmers access new markets. Researchers should keep study the effect of market access in the adoption of new technologies to promote the long-term sustainability of agriculture.

Since markets tend to be regional, results from this study suggest that policies and strategies should focus on specific regions. For example, farmers located in the Midwest are less likely to adopt value-added technologies. One explanation for this may be that the lack of high-populated areas and markets may deter farmers from adopting new technologies. These results show the heterogeneity in the country regions; hence, program and incentives targeting value-added adoption should be at the region or state level to improve their efficiency.

The study also contributes to the diversification literature by proving, with an instrumental variable probit regression, that the decision to diversify horizontally (i.e., producing more crops) is not endogenous to adopt value-added technologies. These results suggest that horizontal diversification helps spread risk through more crops, improves the cash flow, and increases agronomic and financial resilience (McNamara and Weiss, 2005), and drives farmers' decision to adopt value-added technologies. These results show that programs aimed to support crop diversification and market access, such as the USDA Sustainable Agricultural Research and Education (SARE) program, will also influence the adoption of value-added technologies in the specialty crop industry. Extension personnel might promote the increasing of the farmers' crop mix to promote the adoption of value-added technologies.

Labor plays a crucial role in the decision to adopt value-added technologies. We found that, on average, agricultural operations that adopted value-added technologies are more labor-intensive than their counterparts. In other words, the more people working on the farm, the higher the likelihood to adopt value-added. We can infer that the attraction of new people to agriculture may increase the possibility of the adoption of value-added technologies. Although we may find this result as a positive impact, in some cases, labor can be a barrier to add value to raw agricultural products. Due to the lack of financial resources, small farmers can find it difficult to hire more employees. In other cases, farmers may have the resources, but there may be difficulties finding qualified labor to adopt these technologies. Policymakers can use our results to promote employment growth in agriculture (e.g., facilitating the hiring processes of agricultural workers) and support the adoption of value-added technologies at the same time. Our results are consistent with Lobao and Stofferahn (2008), who conducted a seventy years of research review empathizing the vital link between community economic growth and family-organized farms. Extension personnel can communicate to farm owners the positive impact of including family labor in their agricultural operations. The more family involved in the farming business, the more likelihood of VA technologies adoption. Researchers find the interesting continuation of family farming despite all the elements working against it. Even though family farms typically were not in the position to take the advantage of being either big or small (Stevenson et al., 2014).

Farm size is an essential factor to consider when efforts are made to promote value-added technologies. Our results shed light on the remaining difficulties of farming in the middle. The market access gap may be deterring medium-size farmers from adopting value-added technologies. If wholesale stores are focused on large farms to lower operational costs, medium farmers should create more associations to gather their harvest and create better wholesale market opportunities. On the other hand, more direct-to-consumer initiatives should provide medium farmers more options to sell their produce in these market outlets. We can infer by our results that providing market diversification options to farmers will increase the likelihood of adopting value-added technologies and food labels. According to Brekken et al. (2019), medium farmers can increase their economic inputs by adopting values-based supply chain marketing channels such as locally, quality, environmental, and healthy claims differentiation strategies, similar to VA technologies.

The significant contribution of this study is the empirical evidence of the drivers and barriers to adopting value-added technologies and food labels among specialty crops farmers. These results shed light on how farmers might adopt food labels after the adoption of value-added technologies. We can infer that farmers are doing their best to communicate about their agricultural operations and trying to get price premium with these strategies to increase their revenue. Results from this study can be helpful to further research and Extension work.

The implications of this study may be appealing given that there is already a push and a pull effect driving the adoption of value-added technologies. On the one hand, farmers can become more aware that, on average, adopting value-added technologies can increase sales and employment. On the other hand, Extension specialists might be mindful of the factor to consider when making value-added programs more effective. Since value-added technology research has been more focused on international agriculture, this study can motivate scholars to conduct value-added research in U.S. agriculture.

Although we shed light on the drivers of value-added technologies, there are some limitations to this study. The data used in this study was collected through a web-based survey. Hence, we are not taking into account farmers without access to the internet. By using a convenience sampling strategy, we are leaving out farmers that do not appear MarketMaker database. The value-added variables observed do not encompass all value-added technologies that farmers can adopt. Further research should provide a broader range of value-added options such as packing strategies, agri-tourism, or bio-fuels development to comprehend the adoption of these technologies better. Besides, time-series data can be fundamental to assess if farmers adopting these technologies keep using them in the future. Further research should also study the availability of these new technologies to farmers in the market.

# APPENDIX A. TABLES

Table 1. Variable list and description

| Variable | Description |
|---|---|
| ***Farmer Demographics*** | |
| College | 1 = individual has college degree or postgraduate work |
| Female | 1 = if farmer is female |
| Minorities | 1 = if farmer is black, African American, American Indian, Asian, Multiracial, or other |
| Years farming | Years of farming |
| Part-time | 1 = if respondent farms part-time |
| ***Farm Characteristics*** | |
| Market diversification index | Diversification index (measured with the Herfindahl index) for number of sales methods denoting the number of methods used to sell products |
| Market distribution index | Diversification index (measured with the Herfindahl index) for distribution sales methods, denoting the percentage sales through each method |
| Number of crops | crops produced |
| Direct-to-consumer markets | 1= if farmer only used direct-to-consumers market channels such as farmers markets, CSA, etc. |
| Family | number of family members working on-farm |
| Employees | number of employees |
| Total land | Total owned and rented land in acres |
| Sole proprietorship | 1 = if the business structure of the farm is a sole proprietorship |
| Medium farm | 1 = if annual gross sales between $100,000 and $250,000 |
| Large farm | 1 = if annual gross sales larger than $250,000 |
| Sales growth | 1 = if gross sales gone up in 2018, 0 otherwise |
| Employment growth | 1 = if number of employees gone up in 2018, 0 otherwise |
| Midwest region | 1 = in Illinois, Indiana, Iowa, Michigan, Minnesota, North Dakota, and Wisconsin, 0 otherwise |

Table 1 continued

| | |
|---|---|
| ***Networks*** | |
| VA networks | 1= if family, friends and/or farmers in the community have adopted cut or dry strategies in their business |
| Industry associations | 1 = if industry associations were a useful source of information |
| Farmers association | 1 = if other farmers were a useful source of information |
| University Extension | 1 = if university extension was a useful source of information |
| ***Perceptions*** | |
| Government support | 1 = if farmer somewhat or strongly agree that farmers should receive government support to add value to produce |
| Financial assistance | 1 = if farmer somewhat or strongly agree that farmers should receive financial assistance to be able to accommodate the changing regulatory landscape |
| Satisfied | 1 = if farmer somewhat or strongly agree with the satisfaction of the farm business. |
| Positive VA experience | 1 = if farmer somewhat or strongly agree that have they had a positive experience with trying new farming technologies to increase the profits |
| Hard to find VA customers | 1 = if farmer somewhat or strongly agree that it is hard to find reliable customers for value-added produce |

Table 2. Variable means by producer type.

| | Full sample | | | Y=0 N= 265 | | | Y=1 N= 293 | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **N Obs** | **Mean** | **Std. Dev** | **N Obs** | **Mean** | **Std. Dev** | **N Obs** | **Mean** | **Std. Dev** | |
| Market diversification index | 558 | 0.43 | 0.31 | 265 | 0.33 | 0.32 | 293 | 0.52 | 0.28 | *** |
| Market distribution index | 558 | -0.50 | 3.91 | 265 | -0.32 | 1.50 | 293 | -0.66 | 5.20 | |
| Direct-to-consumer markets | 558 | 0.39 | 0.49 | 265 | 0.39 | 0.49 | 293 | 0.38 | 0.49 | |
| College | 523 | 0.66 | 0.47 | 247 | 0.64 | 0.48 | 276 | 0.67 | 0.47 | |
| Female | 522 | 0.33 | 0.47 | 246 | 0.26 | 0.44 | 276 | 0.38 | 0.49 | ** |
| Minorities | 558 | 0.06 | 0.24 | 265 | 0.06 | 0.23 | 293 | 0.06 | 0.24 | |
| Midwest region | 518 | 0.52 | 0.50 | 244 | 0.54 | 0.50 | 274 | 0.50 | 0.50 | |
| Number of crops | 558 | 14.28 | 14.61 | 265 | 7.57 | 11.01 | 293 | 20.35 | 14.83 | *** |
| Years farming | 526 | 23.66 | 15.65 | 249 | 24.76 | 15.73 | 277 | 22.66 | 15.54 | |
| Family | 558 | 2.72 | 1.77 | 265 | 2.61 | 1.64 | 293 | 2.83 | 1.87 | |
| Employees | 558 | 15.16 | 42.01 | 265 | 13.14 | 31.01 | 293 | 16.97 | 49.91 | |
| Total land | 524 | 277.67 | 742.64 | 248 | 321.28 | 855.82 | 276 | 238.49 | 622.70 | |
| Sole proprietorship | 558 | 0.41 | 0.49 | 265 | 0.42 | 0.49 | 293 | 0.41 | 0.49 | |
| Part-time | 558 | 0.32 | 0.47 | 265 | 0.37 | 0.48 | 293 | 0.29 | 0.45 | ** |
| Medium farm | 558 | 0.13 | 0.33 | 265 | 0.14 | 0.34 | 293 | 0.12 | 0.32 | |
| Large farm | 558 | 0.23 | 0.42 | 265 | 0.24 | 0.43 | 293 | 0.23 | 0.42 | |

Table 2 continued

| Variable | Full sample | | | Y=0 N= 265 | | | Y=1 N= 293 | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **N Obs** | **Mean** | **Std. Dev** | **N Obs** | **Mean** | **Std. Dev** | **N Obs** | **Mean** | **Std. Dev** | |
| Sales growth | 558 | 0.34 | 0.47 | 265 | 0.30 | 0.46 | 293 | 0.37 | 0.48 | * |
| Employment growth | 558 | 0.15 | 0.35 | 265 | 0.12 | 0.32 | 293 | 0.17 | 0.38 | * |
| VA networks | 558 | 0.27 | 0.45 | 265 | 0.17 | 0.38 | 293 | 0.37 | 0.48 | *** |
| Industry associations | 517 | 0.69 | 0.46 | 247 | 0.73 | 0.44 | 270 | 0.65 | 0.48 | ** |
| Farmers association | 521 | 0.88 | 0.33 | 247 | 0.86 | 0.35 | 274 | 0.89 | 0.31 | |
| University Extension | 523 | 0.83 | 0.37 | 246 | 0.85 | 0.36 | 277 | 0.82 | 0.39 | |
| Government support | 529 | 0.34 | 0.48 | 248 | 0.30 | 0.46 | 281 | 0.38 | 0.49 | * |
| Financial assistance | 531 | 0.54 | 0.50 | 250 | 0.48 | 0.50 | 281 | 0.59 | 0.49 | ** |
| Satisfied | 533 | 0.65 | 0.48 | 253 | 0.69 | 0.46 | 280 | 0.61 | 0.49 | ** |
| Positive VA experience | 530 | 0.55 | 0.50 | 251 | 0.49 | 0.50 | 279 | 0.61 | 0.49 | *** |
| Hard to find VA customers | 532 | 0.34 | 0.47 | 252 | 0.27 | 0.45 | 280 | 0.40 | 0.49 | *** |

*, **, ***Significant at P < 0.1, 0.05, or 0.01, respectively.

Table 3. IV Probit reduced-form model.

| **Number of crops** | **Coeff.** | **Std. Err.** | |
|---|---|---|---|
| Farming technologies | 8.80 | 1.43 | *** |
| Market diversification index | 11.72 | 2.20 | *** |
| Market distribution index | -0.08 | 0.14 | |
| Direct-to-consumer markets | 3.03 | 1.33 | ** |
| College | -0.18 | 1.24 | |
| Female | 5.97 | 1.22 | *** |
| Minorities | 0.28 | 2.38 | |
| Midwest region | 2.44 | 1.16 | ** |
| Years farming | -0.01 | 0.04 | |
| Family | 0.00 | 0.33 | |
| Employees | -0.03 | 0.01 | ** |
| Total land | 0.00 | 0.00 | |
| Sole proprietorship | 1.66 | 1.27 | |
| Part-time | -5.22 | 1.34 | *** |
| Medium farm | -0.83 | 1.76 | |
| Large farm | -1.03 | 1.76 | |
| Sales growth | 2.71 | 1.29 | ** |
| Employment growth | -0.08 | 1.77 | |
| VA networks | 3.80 | 1.27 | *** |
| Industry associations | -2.63 | 1.34 | * |
| Farmers association | 2.69 | 1.85 | |
| University Extension | -3.99 | 1.67 | ** |
| Government support | 0.26 | 1.40 | |
| Financial assistance | -0.26 | 1.39 | |
| Satisfied | -2.40 | 1.23 | * |
| Positive VA experience | -0.16 | 1.22 | |
| Hard to find VA customers | 0.86 | 1.20 | |
| _cons | 3.02 | 3.06 | |
| Number of obs = | | 491 | |
| F(27, 465) = | | 9.06 | |
| Prob > F = | | 0.00 | |
| R-squared = | | 0.3456 | |
| Adj R-squared = | | 0.3074 | |
| Root MSE = | | 12.15 | |

Table 4. Standard Probit and IV Probit Results for VA technologies adoption.

| | Probit | | | | IV Probit | | |
|---|---|---|---|---|---|---|---|
| | **Coeff.** | **M. eff.** | **Std. Err.** | | **Coeff.** | **Std. Err.** | |
| Market diversification index | 0.98 | 28.69% | 0.26 | *** | 0.73 | 0.38 | * |
| Market distribution index | -0.01 | -0.32% | 0.02 | | -0.01 | 0.02 | |
| Direct-to-consumer markets | 0.34 | 9.94% | 0.16 | ** | 0.29 | 0.17 | * |
| College | -0.05 | -1.57% | 0.15 | | -0.06 | 0.15 | |
| Female | 0.09 | 2.50% | 0.15 | | -0.01 | 0.18 | |
| Minorities | -0.25 | -7.42% | 0.28 | | -0.23 | 0.28 | |
| Midwest region | -0.19 | -5.51% | 0.14 | | -0.22 | 0.14 | |
| Number of crops | 0.04 | 1.09% | 0.01 | *** | 0.05 | 0.02 | *** |
| Years farming | 0.00 | 0.02% | 0.00 | | 0.00 | 0.00 | |
| Family | 0.11 | 3.22% | 0.04 | *** | 0.11 | 0.04 | *** |
| Employees | 0.00 | 0.08% | 0.00 | | 0.00 | 0.00 | * |
| Total land | 0.00 | 0.00% | 0.00 | | 0.00 | 0.00 | |
| Sole proprietorship | 0.06 | 1.83% | 0.15 | | 0.02 | 0.16 | |
| Part-time | 0.04 | 1.22% | 0.16 | | 0.12 | 0.18 | |
| Medium farm | -0.38 | -11.31% | 0.21 | * | -0.37 | 0.21 | * |
| Large farm | -0.04 | -1.17% | 0.21 | | -0.04 | 0.21 | |
| Sales growth | 0.00 | -0.05% | 0.15 | | -0.07 | 0.17 | |
| Employment growth | 0.44 | 13.02% | 0.20 | ** | 0.44 | 0.21 | ** |
| VA networks | 0.47 | 13.68% | 0.15 | *** | 0.38 | 0.18 | ** |
| Industry associations | -0.25 | -7.22% | 0.16 | | -0.21 | 0.16 | |
| Farmers association | -0.06 | -1.73% | 0.21 | | -0.10 | 0.22 | |
| University Extension | -0.07 | -2.13% | 0.20 | | -0.01 | 0.21 | |
| Government support | 0.17 | 5.06% | 0.16 | | 0.17 | 0.17 | |
| Financial assistance | 0.01 | 0.43% | 0.16 | | 0.01 | 0.16 | |
| Satisfied | -0.30 | -8.68% | 0.14 | ** | -0.25 | 0.15 | * |
| Positive VA experience | 0.24 | 7.03% | 0.14 | * | 0.22 | 0.14 | |
| Hard to find VA customers | 0.42 | 12.48% | 0.14 | *** | 0.40 | 0.15 | *** |
| _cons | -1.30 | | 0.36 | *** | -1.38 | 0.38 | *** |
| N. Obs | | | 491 | | | 491 | |
| Prob > chi2 | | | 0.00 | | | 0.00 | |
| Log likelihood | | | -253.8 | | | - | |
| Pseudo R2 | | | 0.25 | | | - | |
| Wald test of exogeneity (corr = 0): chi2(1) | | | | | | 0.83 | |

Table 5. Multinomial Probit Regression and Ordered Probit Regression for VA technologies adoption.

| | **Multinomial Probit Regression** | | | | | | **Ordered Probit Regression** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Y = 1 (N= 161) VA** | | | **Y = 2 (N= 132) VA and Labels** | | | **VA and Marketing** | | |
| | **Coef.** | **M. eff.** | | **Coef.** | **M. eff.** | | **Coef.** | **M. eff.** | |
| Market diversification index | 1.17 | 12.21% | *** | 1.51 | 17.32% | *** | 0.93 | 22.39% | *** |
| Market distribution index | -0.02 | -1.85% | | 0.15 | 2.96% | | 0.00 | -0.09% | |
| Direct-to-consumer markets | 0.56 | 10.51% | ** | 0.24 | -0.87% | | 0.21 | 5.08% | |
| College | 0.00 | 1.68% | | -0.17 | -3.20% | | -0.07 | -1.69% | |
| Female | 0.07 | -0.01% | | 0.16 | 2.46% | | 0.09 | 2.28% | |
| Minorities | -0.19 | 0.78% | | -0.52 | -8.10% | | -0.29 | -6.91% | |
| Midwest region | -0.15 | -0.04% | | -0.34 | -5.03% | | -0.22 | -5.26% | * |
| Number of crops | 0.04 | 0.45% | *** | 0.05 | 0.62% | *** | 0.03 | 0.74% | *** |
| Years farming | 0.00 | 0.07% | | 0.00 | -0.04% | | 0.00 | 0.00% | |
| Family | 0.15 | 2.21% | ** | 0.13 | 1.01% | ** | 0.08 | 1.86% | ** |
| Employees | 0.00 | 0.00% | | 0.00 | 0.07% | * | 0.00 | 0.07% | ** |
| Total land | 0.00 | 0.00% | | 0.00 | 0.00% | | 0.00 | 0.00% | |
| Sole proprietorship | 0.07 | 0.25% | | 0.13 | 1.89% | | 0.05 | 1.15% | |
| Part-time | 0.18 | 5.61% | | -0.16 | -4.74% | | -0.02 | -0.46% | |
| Medium farm | -0.37 | -2.51% | | -0.62 | -8.18% | * | -0.39 | -9.37% | ** |
| Large farm | -0.18 | -5.17% | | 0.11 | 3.81% | | 0.00 | 0.08% | |
| Sales growth | -0.14 | -5.27% | | 0.20 | 5.19% | | 0.12 | 2.83% | |
| Employment growth | 0.64 | 9.83% | ** | 0.50 | 3.25% | | 0.30 | 7.23% | * |
| VA networks | 0.49 | 3.60% | ** | 0.77 | 9.96% | *** | 0.39 | 9.26% | *** |
| Industry associations | -0.44 | -8.91% | * | -0.12 | 2.03% | | -0.11 | -2.69% | |
| Farmers association | -0.06 | -0.02% | | -0.15 | -2.20% | | -0.07 | -1.74% | |
| University Extension | -0.23 | -6.54% | | 0.11 | 4.49% | | 0.05 | 1.22% | |
| Government support | 0.13 | -0.31% | | 0.33 | 5.04% | | 0.14 | 3.45% | |
| Financial assistance | -0.01 | -1.19% | | 0.10 | 2.01% | | 0.06 | 1.43% | |

Table 5 continued

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Satisfied | -0.56 | -11.93% | *** | -0.09 | 3.69% | | -0.14 | -3.29% | |
| Positive VA experience | 0.35 | 5.71% | * | 0.24 | 1.07% | | 0.19 | 4.53% | |
| Hard to find VA customers | 0.45 | 3.18% | ** | 0.72 | 9.39% | *** | 0.39 | 9.49% | *** |
| Intercept | -1.83 | | *** | -2.95 | | *** | | | |
| | | | | | | | | | |
| /cut1 | | | | | | | 1.26 | | |
| /cut2 | | | | | | | 2.25 | | |
| Number of observations | | | | | 491 | | 491 | | |
| Log likelihood | | | | | -413.53 | | -431.45 | | |
| Pseudo R2 | | | | | | | 0.17 | | |
| Prob > chi2 | | | | | | | 0.00 | | |
| LR test P-value | | | | | | | 0.18 | | |
| AIC | | | | | 939.06 | | 920.91 | | |
| BIC | | | | | 1174.06 | | 1042.61 | | |

*, **, ***Significant at P < 0.1, 0.05, or 0.01, respectively.

Base: Y=0 (N=265) Non-Value-added operations

# APPENDIX B. SURVEY LETTER

Dear specialty crop grower,

Consumer demand for fresh produce has been growing in the recent years as consumers are looking for more local foods. We are conducting this survey among produce growers to better understand your production and marketing challenges. We are pleased to provide an incentive of $10 Amazon gift card to the first 1,000 farmers who complete the survey, as a thank you for your valuable time and knowledge.

This survey will help us identify production and marketing needs to develop research and extension information for growers like you.

By taking this survey, you will help us to identify ways we can help farmers like you to boost farm income. We will be publishing the study results in Purdue Extension publications, and other publicly available outlets. Information from this study can help inform policymakers, state legislators, and industry stakeholders.

You have been randomly selected to represent growers in your local area by sharing your experiences and views. Your responses are important because you will be representing your neighbors as well as yourself. The survey should take approximately 10-20 minutes.

We are interested in knowing your "value-added" activities, which includes the following practices that add value to specialty crops: Changing its physical state: washing, cutting to customer-ready portion, or drying produce. Marketing its special identity: organic, non-GMO, state-produced labels, etc.

Specialty crops are defined as fruits, vegetables, culinary herbs, and horticulture crops. Your answers will be kept confidential and anonymous. The only results shared will combine answers from everyone in the survey. If you have questions or concerns, please contact me to: Dr. Ariana Torres; Assistant Professor and Marketing Specialist; telephone: 765-494-8781; email: torres2@purdue.edu.

Thank you very much for your cooperation. Your help is greatly appreciated.

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